Image Segmentation using Quantum Particle Swarm Optimization

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Abstract: This paper presents a novel image segmentation algorithm, which uses a biologically inspired paradigm known as swarm intelligence to segment images. A more efficient MRF based clustering algorithm that incorporated the Markov Random Field (MRF) theory and the Quantum Particle Swarm Optimization (QPSO) algorithm is proposed. The QPSO algorithm is used to optimize the energy function which is a combinatorial optimization problem because of the large search space. The QPSO algorithm has few parameters and is simpler and more powerful than the classical version of the Particle Swarm Optimization algorithm. The experiments performed on both synthetic and real images show that the QPSO-MRF algorithm generates good results in clustering images and outperforms those obtained with other optimization methods.

Key words: Image segmentation; Markov Random Field, Optimization, Quantum Particle Swarm Optimisation.

INTRODUCTION

Image segmentation is a low-level image processing task in a vision system. It has been the subject of intensive research, and a wide variety of image segmentation techniques have been reported in the literature. A good review of these methods can be found in [PAL 93]. Among them, Markov Random Field (MRF) is one of the most frequently utilized techniques [AND 98],[CHE 95],[GEM 84],KER 95]. MRF has been shown to be quite successful for image segmentation because of its ability to characterize spatial relations among image pixels by conditional probability over small neighborhoods of pixels. The image is segmented by maximizing the a posteriori probability of the labeling space given the image data [GEM 94]. Within this framework, the segmentation process is expressed as the problem of finding the optimum value of an energy function [GUN 94],[KIM 00],[LI 95]. This is a combinatorial optimization problem because of the large search space. Moreover, the energy function is usually non-convex and exhibits many local minima in the solution space.

As a result, techniques such as iterated conditional method (ICM) [BEZ 86],[PAN 95], genetic algorithm (GA) [AND 98],[GUN 94],[HUN 95], [LI 93] and simulated annealing (SA) [KIM 00] have been often used as solution for this computational complexity.

Particle Swarm Optimization (PSO) algorithm is an optimization technique [KEN 95] that has been recently proposed to solving the clustering problems [OMR 05], [RUN 06], [SWA 06]. Despite the capability to PSO to find good solutions compared to classical optimization methods, it has been proven that it can’t guarantee convergence to the global best solution [SHI 99]. In order to improve the performance of the PSO algorithm, a number of improvements have been introduced to the classical PSO algorithm. In [SUN 04a], [SUN 04b] authors proposed Quantum Particle Swarm Optimization (QPSO) algorithm in which particles can search for the whole quantum’s space, and so have a higher convergent capability of the global optimizing than in PSO algorithm. So in this paper, a QPSO-MRF algorithm that incorporates the Markov Random Theory into the QPSO algorithm is proposed.

The paper is organized as follows. Section 2 presents a brief review on image modeling using MRF theory. Section 3 describes QPSO algorithm. Section 4 presents the proposed QPSO-MRF algorithm. In section 5 we present the experimental results and we compare QPSO-MRF with other heuristics. Finally a conclusion is drawn in section 6.
1. Image segmentation using Markov Random Field

The MRF was introduced in image analysis by Geman and Geman [GEM 84]. MRF is a stochastic process in which spatial relations within the image are included in the labeling process through statistical dependence among neighboring pixels. Let \( Y = \{ y_s / \forall s \in S \} \) designate an observation field defined on a rectangular lattice \( S \). Let the label field \( X = \{ x_s / \forall s \in S \} \) defined on \( S \) and the set of labels \( \Lambda = \{ 0, \ldots, L - 1 \} \) of the pixel \( s \). Realization of fields \( Y \) and \( X \) will be denoted by \( y = \{ y_s / \forall s \in S \} \) and \( x = \{ x_s / \forall s \in S \} \). \((X, Y)\) is a Markov random field on \( S \) with respect to a neighboring system \( N = \{ N_s, s \in S \} \), where \( N_s \) is the set of pixels neighboring \( s \).

Our goal is to find the best estimated \( \hat{x} \) for \( x \) given \( y \). According to the Maximum A Posteriori (MAP), criterion, \( x \) is obtained by minimizing the global energy function \( U(y; x) \).

\[
\hat{x} = \arg \min_x \{ U(y; x) \} \tag{1}
\]

If we make the assumption that the image data are conditional independent and that \( Y \) is obtained by adding an identical independently distributed (i.i.d.) Gaussian noise, and according to the Hammersley-Clifford theorem, the energy \( U(y; x) \) is formulated as follows [BEZ 86]:

\[
U(x) = \left\{ \frac{\sum_{s \in S} (y_s - \mu_{x_s})^2}{2 \sigma_{x_s}^2} + \sum_{s \in S} \log(\sigma_{x_s}) + \sum_{c \in C} V_c(x) \right\} \tag{2}
\]

where \( \mu_{x_s} \) : the mean value of the cluster \( x_s \)

\( \sigma_{x_s} \) : the deviation value of the cluster \( x_s \)

\( V_c(x) \) : the potential function for clique \( c \)

\( C \) : the set of all cliques over the image.

A clique is a set of pixels that are neighboring of one another. In this paper we consider only the pair site clique potentials of 8-neighborhood system, with the form \( V(x_1, x_2) = -\beta \) if \( x_1 = x_2 \) and 0 otherwise. \( \beta \) is a positive parameter and the larger \( \beta \), the larger is the influence of the neighboring pixels.

Minimization of the global energy function, is hard optimization problem because the number of possible label configurations is generally very large and moreover, the energy function may contains local minima [LI 95], [PAN 95].

2. Quantum particle swarm optimization

The PSO method is a population-based optimization strategy introduced by James Kennedy and Russell C. Eberhart [KEN 95] and has shown its robustness and efficacy in solving many optimization problems. In a PSO algorithm, a swarm of particles cooperate to find an optimal solution to the problem. Each particle represents a point in multidimensional search space and corresponds to a feasible solution of the problem. Different problem solutions are generated by the movements of the particles from a location to another. Each solution is evaluated by a fitness function that provides a quantitative value of the solution’s utility.

The PSO algorithm is initialized with a swarm of \( n \) particles randomly distributed over the search area. Each particle \( i \) is represented by its position \( x_i \) and its velocity \( v_i \). The movement of a particle through the search space is influenced dynamically according to its own personal best position \( p_i \) and its neighbors’ best position \( p_g \). At each iteration \( t \), the particle’s new position and its velocity are changed according to the following update rules:

\[
x_i(t) = x_i(t-1) + v_i(t) \tag{3}
\]

\[
v_i(t-1) = w v_i(t-1) + \varphi_1 \times \text{rand}_1 \ (p_i - x_i(t-1)) + \varphi_2 \times \text{rand}_2 \ (p_g - x_i(t-1)) \tag{4}
\]

The new position of the particle is given by its old position plus its current velocity. The velocity is determined by a combination of three terms. The first term is the speed from the previous iteration step, weighted with an inertia weight \( w \) that decreases linearly from \( w_{\text{min}} \) to \( w_{\text{max}} \). The second term is a cognitive component and represents the particle’s desire to return to its previous best position \( p_i \).

Finally, the third term is a social component that gives the attraction of seeking the best position \( p_g \) among the particle’s topological neighbors. \( \varphi_1 \) and \( \varphi_2 \) are two constants which control the influence of the social and cognitive components. \( \text{rand}_1 \) and \( \text{rand}_2 \) are random values in the range \([0,1] \).

Despite the capability of the classical PSO to overcome other optimization algorithms, it has some problems when it comes to reach a near optimal solution [SHI 99], [SUN 04b]. In order to prevent such a premature convergence, some improved versions of the PSO have been proposed. In [SUN 04a], [SUN 04b] Sun et al. consider that particles have quanta
behavior and proposed Quantum PSO (QPSO) model. For each iteration of QPSO algorithm a particle changes its position in the dimension $d$ according to the following equation:

$$x_{id} = p_{id} \pm \alpha*|mbest_d - x_{id}|*\ln\left(\frac{1}{u}\right)$$

(5)

until (MAXITER is met)

3. QPSO for MRF based image segmentation

In this paper, the MRF based clustering problem is formalized as an optimization problem of the energy function. So the aims of this paper is to propose a more efficient MRF based clustering algorithm using the QPSO paradigm.

In the QPSO-MRF clustering algorithm, a particle represents a set including $N_c$ cluster centers. Each particle represents the $c$ cluster centroids so a swarm of particles represents a set of candidate partitions. Each particle $i$ is coded as $i = \{c_{i1}, c_{i2}, ..., c_{ic}\}$ where $c_{ik}$ represents the $k^{th}$ cluster centroid for the $i^{th}$ particle and $C$ is the number of clusters. The quality of each particle is measured using the objective function described in Eq 2.

The QPSO-MRF clustering algorithm is summarized below:

1. Initialize the swarm of particles with random positions (random cluster centers) referring to the original image.

2. For each particle $i$ do

   a) Calculate the fitness value based on Eq 2.
   b) Record the personal best position.
   c) Record the global best position.
   d) According to the equations (5), (6) and (7), generate the new position for the particle.

3. Record the optimal solution and the global best fitness value of entire swarm.

4. Go to step (2) until the maximum number of iterations is exceeded.

4. Experimental results

In order to validate the proposed QPSO-MRF algorithm, we compare its performance with other methods based on genetic algorithm and simulated annealing. For the comparison, we use noisy synthetic image ad real images presented in Figure 1 and Figure 2.

For $d=1$ to dimension $D$:

$\phi = \text{rand}(0.1), u = \text{rand}(0.1);$

compute $p_{id}$ using Equation 6

if (rand>0.5) $x_{id} = p_{id} - \alpha*|mbest_d - x_{id}|*\ln\left(\frac{1}{u}\right)$

else

The parameters of SA, GA and QPSO-MRF..
algorithms are tabulated in table 1.

<table>
<thead>
<tr>
<th>Algorithms</th>
<th>Parameters</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>SA</td>
<td>$T_0$</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>$T_m$</td>
<td>0.9</td>
</tr>
<tr>
<td></td>
<td>$N_i$</td>
<td>100</td>
</tr>
<tr>
<td></td>
<td>MAXITER</td>
<td>3000</td>
</tr>
<tr>
<td>GA</td>
<td>$N$</td>
<td>30</td>
</tr>
<tr>
<td></td>
<td>$P_c$</td>
<td>0.8</td>
</tr>
<tr>
<td></td>
<td>$P_m$</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>MAXITER</td>
<td>1000</td>
</tr>
<tr>
<td>QPSO-MRF</td>
<td>$M$</td>
<td>30</td>
</tr>
<tr>
<td></td>
<td>$\alpha_1$</td>
<td>1.0</td>
</tr>
<tr>
<td></td>
<td>$\alpha_2$</td>
<td>0.5</td>
</tr>
<tr>
<td></td>
<td>MAXITER</td>
<td>2000</td>
</tr>
</tbody>
</table>

Table 1. Parameters of the Simulated annealing, Genetic algorithm, and QPSO-MRF algorithms.

where $T_0$: initial temperature, $T_m$: temperature multiplier, $N_i$: number of iterations after which temperature is reduced, MAXITER: maximum number of iterations allowed, $N$ the population size, $P_c$: crossover probability, $P_m$: mutation probability, $M$: size of the swarm, $\alpha_1, \alpha_2$ the constringency and expend parameters.

4.1. Synthetic image

To validate the accuracy and reliability of each segmentation method, compared with the ground truth of synthetic image, we computed the Jaccard similarity. The Jaccard similarity measures the similarity of two sets as the ration of the size of their intersection divided by the size of their union. Let $V^g_k$ and $V^s_k$ denotes the total number of pixels labeled into a cluster $k$ in the ground truth (g) and the obtained segmentation (s). For cluster $k$ the Jaccard similarity $J^k(g,s)$ is defined by

$$ J^k(g,s) = \frac{|V^k_g \cap V^k_s|}{|V^g_g \cup V^s_s|} $$  \hspace{1cm} (9) $$

A good segmentation is obtained when $J^k(g,s)$ is near 1 which means that the cluster $k$ is well detected.

For all algorithms, the results reported averages over 25 simulations are given in table 2.

<table>
<thead>
<tr>
<th>Algorithms</th>
<th>Classes</th>
<th>Jaccard similarity</th>
</tr>
</thead>
<tbody>
<tr>
<td>SA</td>
<td>1</td>
<td>0.85</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0.92</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>0.91</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>0.95</td>
</tr>
<tr>
<td>GA</td>
<td>1</td>
<td>0.86</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0.93</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>0.91</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>0.96</td>
</tr>
<tr>
<td>QPSO-MRF</td>
<td>1</td>
<td>0.91</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0.95</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>0.94</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>0.97</td>
</tr>
</tbody>
</table>

Table 2. Performance comparison of the SA, GA, and QPSO-MRF algorithms for segmentation of noisy synthetic image of Figure 1

It is clear that the new algorithm QPSO-MRF outperforms others algorithms and finds better results.

4.2. Real images

QPSO-MRF algorithm has been applied to two gray level real world images representing a muscle cell image and a house image, presented in Figure 2.

Figure 2. real world images. a) muscle cells image, b) a house image

To quantitatively evaluate the quality of the different clustering algorithms, without need to a ground truth, we use a simplified version of the Borsotti measure [BOR 98], which was defined as follows:

$$ Q(I) = \frac{1}{1000(N)} \sqrt{R \sum_{k=1}^{K} \left[ \frac{e^2_k}{\sqrt{A_k}} \right]} $$  \hspace{1cm} (10) $$

where:

$I$: image to be segmented;

$N$: size of the image;
$R$ : number of clusters in the segmented image;
$A_k$ : area, or the number of pixels of the $k^{\text{th}}$ cluster;
$e_k$ : gray level error of cluster $k$.

$e_k$ is defined as sum of the square of the Euclidean distances between the gray level intensity of pixels in cluster $k$ and the average gray level intensity of cluster $k$ in the segmented image.

The first term of Eq. (10) is a normalization factor. The smallest the value of $Q(I)$, the better the segmentation results were. Table 3 contained the results obtained from SA, GA, and QPSO-MRF algorithms.

<table>
<thead>
<tr>
<th>Images</th>
<th>(a)</th>
<th>(b)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SA</td>
<td>1.130</td>
<td>0.980</td>
</tr>
<tr>
<td>GA</td>
<td>1.128</td>
<td>0.950</td>
</tr>
<tr>
<td>QPSO-MRF</td>
<td>1.1262</td>
<td>0.9354</td>
</tr>
</tbody>
</table>

Table 3. Borsotti & al. Measure ($Q$) comparison for real images $(a)$ and $(b)$

As we can see, QPSO-MRF obtained good quality segmentation results

5. Conclusion

In this paper an optimization algorithm based on quantum individual behavior of particles is proposed to resolve the MRF based image segmentation. It is simpler and more powerful than others optimization methods because the QPSO is a global convergent optimization algorithm. Simulation experiments also proved its efficiency and good performance compared to others heuristics like SA and GA algorithms.

REFERENCES
